Abstract:

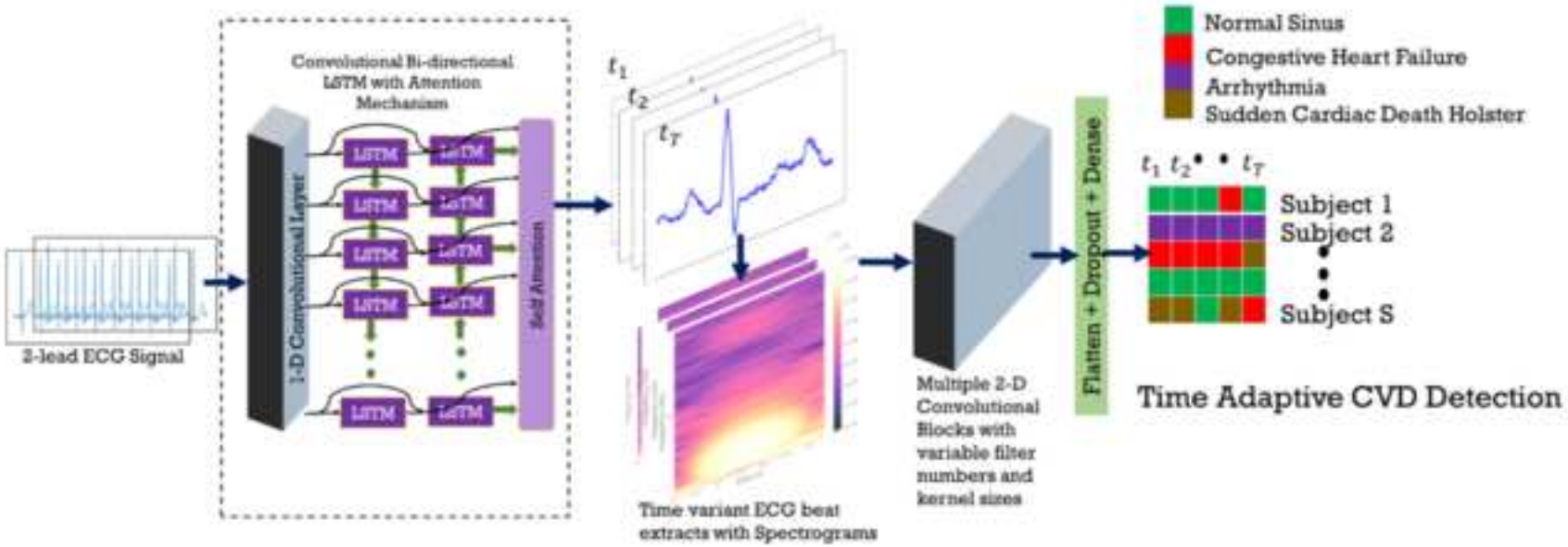
Electrocardiograms (ECGs) are widely used to detect cardiovascular disease (CVD). Deep learning is a topic of interest in healthcare, in which timely detection of ECG anomalies can play a vital role in patient monitoring. However, automatic detection of CVD via ECGs is a complex problem, where state-of-the-art performance is achieved typically by the rule-based diagnosis models, which are inefficient to deal with large amount of heterogeneous data and requires significant analysis and medical expertise to achieve adequate precision in CVD diagnosis.

In this paper, we propose a two-stage multiclass algorithm. The first stage performs ECG segmentation based on Convolutional Bidirectional Long Short-Term Memory neural networks with attention mechanism. A second stage is based on a time adaptive Convolutional Neural networks applied to ECG beats extracted from first stage for several time intervals. ECG beats are converted to 2D images using Short-Time Fourier Transform to automatically discriminate normal ECG from cardiac adverse events such as arrhythmia and congestive heart failure and predict sudden cardiac death. Model accuracy was compared across different time scales. Data used to train and test the models were extracted from MIT/BIH-PhysioNet databases.

By using 4 minutes ECG, we achieved an accuracy of 100% to automatically detect congestive heart failure events, 97.9% for arrhythmia events, and 100% to predict sudden cardiac deaths. This offers unprecedented results by supporting domain-experts work, by computing signal characteristics via an automated complete system for CVD diagnosis. The achieved results showed to be promising compared to state-of-the-art algorithms used for similar purposes.

Key words: ECG; deep learning; cardiovascular disease; arrhythmia; congestive heart failure; sudden cardiac death

Graphical Abstract



Highlights

- We propose a two-stage multiclass algorithm to automatically predict CVD
- The first stage extracts ECG beats via Convolutional Bi-directional LSTM
- Each ECG beats are converted to 2D spectrograms using Short-Time Fourier Transform
- 2D-CNN deployed to time variant spectrograms for several time intervals
- High accuracy is achieved to automatically detect CHF, ARR and SCD

Time Adaptive ECG driven Cardiovascular Disease Detector

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Abstract:

Electrocardiograms (ECGs) are widely used to detect cardiovascular disease (CVD). Deep learning is a topic of interest in healthcare, in which timely detection of ECG anomalies can play a vital role in patient monitoring. However, automatic detection of CVD via ECGs is a complex problem, where state-of-the-art performance is achieved typically by the rule-based diagnosis models, which are inefficient to deal with large amount of heterogeneous data and requires significant analysis and medical expertise to achieve adequate precision in CVD diagnosis.

In this paper, we propose a two-stage multiclass algorithm. The first stage performs ECG segmentation based on Convolutional Bidirectional Long Short-Term Memory neural networks with attention mechanism. A second stage is based on a time adaptive Convolutional Neural networks applied to ECG beats extracted from first stage for several time intervals. ECG beats are converted to 2D images using Short-Time Fourier Transform to automatically discriminate normal ECG from cardiac adverse events such as arrhythmia and congestive heart failure and predict sudden cardiac death. Model accuracy was compared across different time scales. Data used to train and test the models were extracted from MIT/BIH-PhysioNet databases.

By using 4 minutes ECG, we achieved an accuracy of 100% to automatically detect congestive heart failure events, 97.9% for arrhythmia events, and 100% to predict sudden cardiac deaths. This offers unprecedented results by supporting domain-experts work, by computing signal characteristics via an automated complete system for CVD diagnosis. The achieved results showed to be promising compared to state-of-the-art algorithms used for similar purposes.

Key words: ECG; deep learning; cardiovascular disease; arrhythmia; congestive heart failure; sudden cardiac death

1 Introduction

Since the twentieth century, electrocardiogram (ECG) analysis is the core of cardiovascular pathology diagnosis. The ECG signal reflects the electrical activity of the heart, and its waveform alteration or heart rhythm disorders are evidences of underlying cardiovascular problems [1]. These alterations may be progressive and can potentially lead to pathological changes in cardiac structure or function, which can eventually lead to clinically relevant cardiovascular disease (CVD) [2]. CVDs are one of the most common chronic and life-threatening group of disease and, therefore, one of the main causes of mortality [3].

Among CVDs, congestive heart failure (CHF) and myocardial infarction are complex clinical syndrome and poses a serious threat to human health. Those diseases can lead to sudden cardiac death (SCD) often initiated with a sustained arrhythmia (ARR) such as ventricular tachyarrhythmia, including ventricular tachycardia (monomorphic or polymorphic), ventricular flutter, or ventricular fibrillation [4]. Sudden cardiac death syndrome may be also due to a wide variety of different electrical and mechanical substrates, including but not limited to chronic coronary disease with prior myocardial infarction(s), valvular heart disease, and the long Q-T syndrome [5]. Therefore, it is of paramount importance to monitor ECG signals for early diagnosis of heart rhythm disorder (e.g., arrhythmia) and CHF for assessing their severity and early prediction of SCD. However, since the ECG perturbations may be subtle, it could be difficult for clinical experts to detect the differences of ECGs [2]. Early detection of ARR and CHF usually requires long-term ECG monitoring (more than 24 h), but to provide an effective treatment, ARR, CHF and SCD need to be diagnosed in a shorter time [6, 7].

Recently, there have been many developments and approaches for computer-aided ECG adverse events classification [8]. The fast development of Big Data and Internet of Things industry has brought improvements in medical devices, data acquisition and diagnosis, which can be assisted by computer-aided methods [9-11]. Most computer-aided ECG classification approaches are characterized by the pre-processing of ECG signal, heartbeat detection, feature extraction and selection, and lastly the classifier construction [1, 12]. In this article, we emphasized the need of a complete, reliable system for heartbeat detection, post-processing analysis and classification for automated detection of CVD in short time windows, by reducing the need of highly demanding signal processing and feature extraction/selection.

The pre-processing of the ECG signal and the heartbeat detection have been widely studied, and the heartbeat detection has achieved optimal results in the recent years [13]. There are two categories of extracting ECG-segment related features, i.e., i) *ECG localization* and ii) *ECG segmentation*. *ECG localization* algorithms are related to locate ECG related landmarks (such as starting, ending and peak points of P, QRS and T waves). On the other hand, *ECG segmentation* performs segmentation of the waves, resulting in extracting individual beats. Most of the existing techniques, used to detect ECG waves, are based on traditional signal processing methods such as wavelet transformation, low pass differentiation, and adaptive thresholding. However, these methods are less robust in detecting and featuring ECG segments across different heart conditions [14]. Deep learning approaches have shown promising results in order to detect and segment ECG beats [15]. Out of different deep learning architectures, Convolutional Neural Networks (CNNs) have been deployed to extract local features of ECG waves from the ECG signal and they have been quite successful in localization of the P,QRS and T waves [16]. Although several studies have proposed automatic ECG segmentation tools [13, 15-18], there is still space to improve the proposed algorithms.

Nevertheless, electrocardiogram signals and beats are sensitive to noise. Therefore, previous studies suggest the conversion of ECG signal into frequency domain prior to ECG classification algorithms. Commonly used methods for the frequency analysis of signals are short-time Fourier transform (STFT), discrete cosine transform (DCT), continuous wavelet transform (CWT), and discrete wavelet transform (DWT) [19, 20]. By transforming signal from time domain to frequency domain using the frequency analysis, the 1-D signal becomes a 2-D matrix, and it can be analyzed on multiresolution. Few studies have investigated ARR and CHF events by transforming ECGs signals and/or beats using frequency analysis [21-24].

Previous studies have developed computer-aided design systems with traditional machine-learning (ML) algorithms using ECG signals for ARR, and CHF diagnosis [25, 26]. However, traditional ML methods require hand-crafted features, which must be derived from trial and error to achieve optimal classification accuracy. For useful and accurate classification, it is necessary to determine which visual features best represent the ECG signal for extraction. Therefore, ECG signal classification without feature extraction should be examined further. In this scenario, deep learning algorithms have been explored to overcome the abovementioned issues [23, 25, 27-31]. In particular, CNN, an intricate structure which comprises many masked deep layers and parameters, has also been successfully used to detect heart disease among many

other medical disease [32-34]. CNN encompasses several stages including the convolution stage where features are extracted from the input signals, the rectified linear activation stage where non-linearity in the data is charted, the pooling stage where features and computational complexities are reduced, and the fully-connected layer that sorts the input data into various classes according to the data used for training [26].

In this study, we propose a complete system for 1) ECG segmentation using a time adaptive Convolutional Long Short-Term Memory (LSTM) neural network with attention mechanism to facilitate an ECG driven cardiovascular disease detector; 2) a time-adaptive CNN for ECG beats converted to spectrogram (2D image) using Short-Time Fourier Transform to detect cardiac adverse events such as ARR and CHF and to predict SCD. The attention mechanism is able to automatically segment ECG beats in different time windows based on both time variant and local ECG features while self-correlating the ECG sequences in order to facilitate a time adaptive ECG driven cardiovascular disease detector. On the other hand, time adaptive CNN can detect and predict different heart conditions based on spectrograms of ECG beats extracted for limited time interval.

To the best of our knowledge, this paper is the first to present a time adaptive detector for normal sinus rhythm (NSR), CHF, ARR and SCD, via ECG beats extracted through an automated approach and controlled by time. This system can lead to detection of different heart conditions across real-time settings.

2 Material and Methods

The block diagram of time adaptive ECG driven CVD detector is shown in Figure 1. There are two stages to perform automated CVD detection. The first stage performs automated ECG segmentation based on sequential deep learning architecture to determine number of beats adaptive through time. The second stage is based on multi-layered 2D-CNN architecture driven by 2D spectral images obtained after transforming 1D-ECG beats extracted from stage 1 into time-frequency plots.

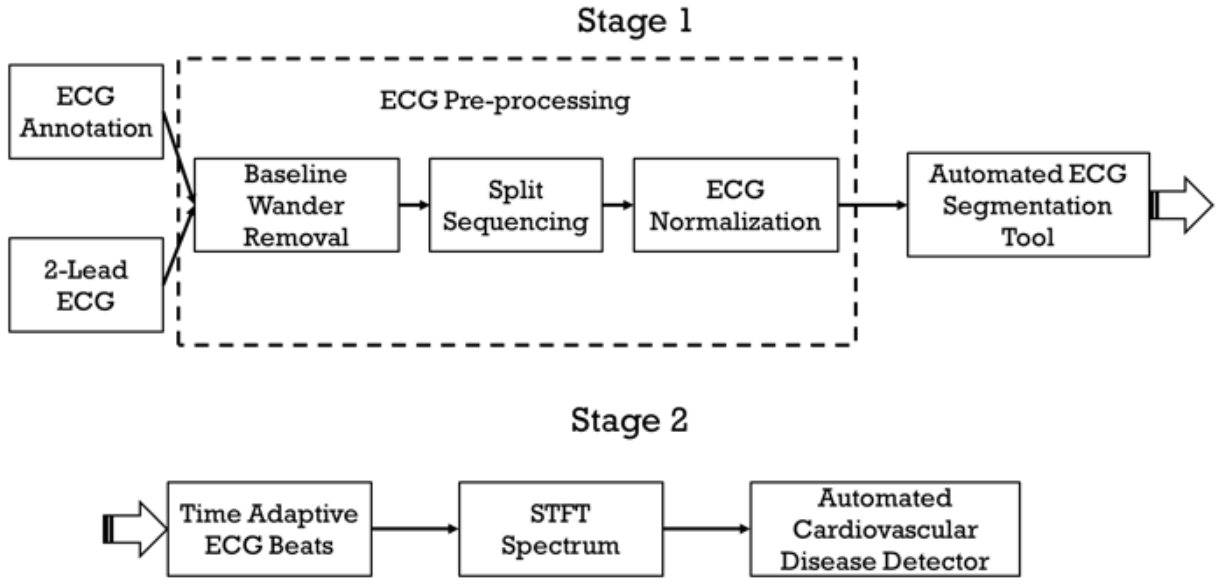

Figure 1. Block Diagram of Time Adaptive ECG driven CVD Detector

The details of the time adaptive ECG driven CVD detector are provided in the following sections.

2.1 Dataset

We used one dataset for training/testing the ECG segmentation model in the first stage and four datasets for CVD model detector training/testing.

The automated ECG segmentation model was trained, validated and tested using PhysioNet's QT database, a dataset of 105 2-lead ambulatory ECG recordings [35], with P, QRS and T waves clearly annotated. The records were chosen from existing ECG databases, including the MIT-BIH Arrhythmia Database, the European Society of Cardiology ST-T Database, and several other ECG databases collected at Boston's Beth Israel Deaconess Medical Center (Supplementary Table 1). Further information can be accessed here https://physionet.org/content/qtdb/1.0.0/. Out of 105 subjects, 11 subjects were excluded as there were no annotations for either of P, QRS or T wave.

Experiments aimed to detect events such as NSR, CHF, ARR and predict SCD. However, CHF, atrial fibrillation and ventricular arrhythmia and sudden death may overlap in the same patients. Although we carefully explored the signals to identify potentials overlapping, these conditions were not mutually exclusive in the used datasets. Four publicly available datasets available from Physionet were used: 1) MIT-BIH Normal Sinus Rhythm Database including 18 long-term ECG recordings of normal healthy not-arrhythmic subjects (i.e., control group) (Females = 13; age range: 20 to 50) [36]; 2) BIDMC Congestive Heart Failure Database, including 15 long-term ECG recordings of subjects with severe CHF (i.e., NYHA classes III-IV) (Females = 4; age range: 22 to 63) [37]; 3) MIT-BIH Sudden Cardiac Death Holter database, including 18 patients with sustained ventricular tachyarrhythmia. We excluded six subjects with non-audited attributes. Most patients had an actual cardiac arrest (Females= 8; age range: 17 to 89) [36, 38]; 4) MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects (F=22; age range: 23 to 89) [39]. Further information can be accessed here [36-39].

2.2 Stage 1: Automated ECG Segmentation Tool

The purpose of the automated ECG segmentation tool is to extract the individualized ECG beats to determine key features associated with the difference among multiple heart conditions. The accurate extraction of individualized heartbeats is subject to removal of the noise from the ECG signal. Before deploying the deep learning architecture, we performed noise removal from the signal as well as signal normalization. For training the automated ECG segmentation tool, we deployed QT database in which minimum samples among the examples are 3500 data points. Besides, sequential gaps in annotations across many examples also exist. The minimum data points from an example with annotation was 1300.

2.2.1 ECG Pre-processing

The pre-processing of the ECG was performed to remove noise and to standardize across all the training examples. Three pre-processing steps were performed:

i. Baseline Wander Removal. Baseline wander is low frequency noise in the ECG signal arising from breathing, electrically charged electrodes or subject movement resulting in a variable electrical isoline. In order to remove the baseline wanders, there have been several techniques proposed [40]. We adopted wavelet based technique which has been one of the successful techniques of baseline wander removal from the ECG signal [41]. Following this technique, we decomposed the ECG signal into low and high frequency components using Daubechies wavelet transform to level 8 and reconstructed the signal after removing the lowest frequency component. The results are shown in Figure 2. Wavelet transforms have performed significantly better compared to earlier techniques of Butterworth low frequency filtering [40].

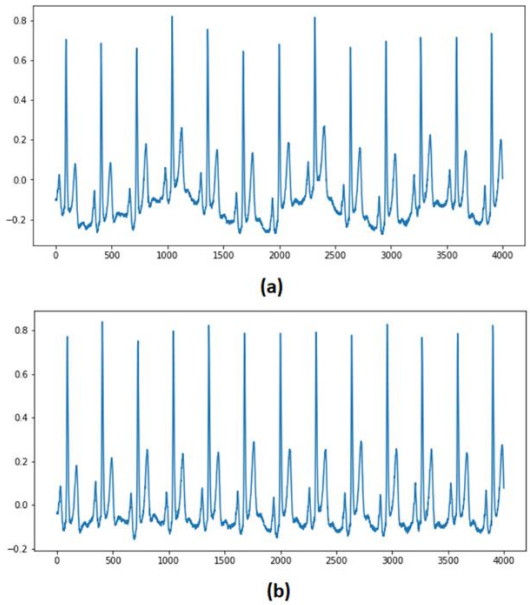

Figure 2. Effect of Baseline Removal with (a) Original ECG signal and (b) ECG signal with baseline wander removal

ii. ECG splitting. In the second step, we performed the splitting of the ECG signal into equal size samples. This was performed to train the sequential deep learning architecture with segment labels. Considering the minimum number of data points with annotations we can get from QT database we selected a chunk of 1000 data points with 150 data points pre and post chunk for continuation in longer ECG signals; making a total of 1300 data points.

iii. Normalization. In the third step, we performed z-score normalization to standardize each ECG signal at zero mean and unit variance

2.2.2 Automated ECG Segmentation

Our approach is focused on segmenting the entire ECG beat; including P, QRS, T waves as well as gaps in between these waves. These require not only local features but also temporal features. Therefore, we opted to deploy the Recurrent Neural Networks (RNNs) which has the capability to model the sequence of events and predict the information based on occurrence of temporal events [42]. The chain like sequential structures of the RNN connected through time had been used in predicting temporal events based on information occurred previously through time such as speech recognition, natural language processing etc. Among various architectures of the RNNs, Long Short Term Memory (LSTM) architectures were designed to avoid long-term dependency problem occurring in traditional RNNs [43].

In order to acquire both local features as well as time variant features, we designed and deployed Convolutional Bi-directional LSTM architecture to train the segments based on information occurring in both past as well as the future context (Figure 3). We performed 4-class classification obtaining the segments as P, QRS, T, NW (No Wave). We trained the architecture on the ECG samples with 1300 data points obtained from two-lead ECGs, making the feature size of 2. The ECG segmentation tool architecture has 4 blocks:

i) *Convolutional Block*: The input is fed to the 1-D Convolutional block which consists of one-dimensional convolutional layer which convolves in temporal dimension with 32 filters and kernel size = 3 followed by 20% dropout. This can be expressed as equation with x_{1d} as ECG sequence, W_{1d} as 1-D convolutional weights (eq. 1):

$$y_{1d} = [\![Dropout(W)]\!]_{1d} \otimes x_{1d} + b) \quad (1)$$

ii) *LSTM Block*: We then add the LSTM block which is composed of Bi-directional LSTM (BiLSTM) architecture of 32 units empirically selected, resulting in output of 1300 x 64 as output form forward and backward LSTM units are concatenated together. We also add droput layer with 20% dropout followed by batch normalization in order to avoid overfitting problems during training. This can be expressed as (eq. 2):

$$h_t = BN\left(Dropout\left(\left[LSTM\left(y_{1d_t}, \vec{h}_{t-1}\right), LSTM\left(y_{1d_t}, \overleftarrow{h}_{t+1}\right)\right]\right)\right) \quad (2)$$

where $\vec{h}_t$ are $\overleftarrow{h}_t$ are forward and backward LSTM outputs respectively at time t; BN represent bacth normalization.

iii) *Self Attention:* The self-attention layer is an attention mechanism which relates different position of ECG sequences in order to compute abstractive representation. This enables to train the correlation between ECG segment under consideration and the ECG segment occuring in time before/after. The attention weights can be calculated as (eq. 3):

$$\sigma_{max}(z)_i = \frac{e^{dot(h_{t_i}, h_{t_i})}}{\sum_{j=1}^{J} e^{dot(h_{t_i}, h_{t_i})}} \quad (3)$$

where $dot(h_{t_i}, h_{t_i})$ is attention score which is the dot product of LSTM output by itself; σ_{max} the softmax function representing the attention weights.

iv) *Time Distributed Dense Layer:* The main function associated with the Time Distributed Dense Layer is to return the sequences with the segment labels compared to traditional Dense layers.

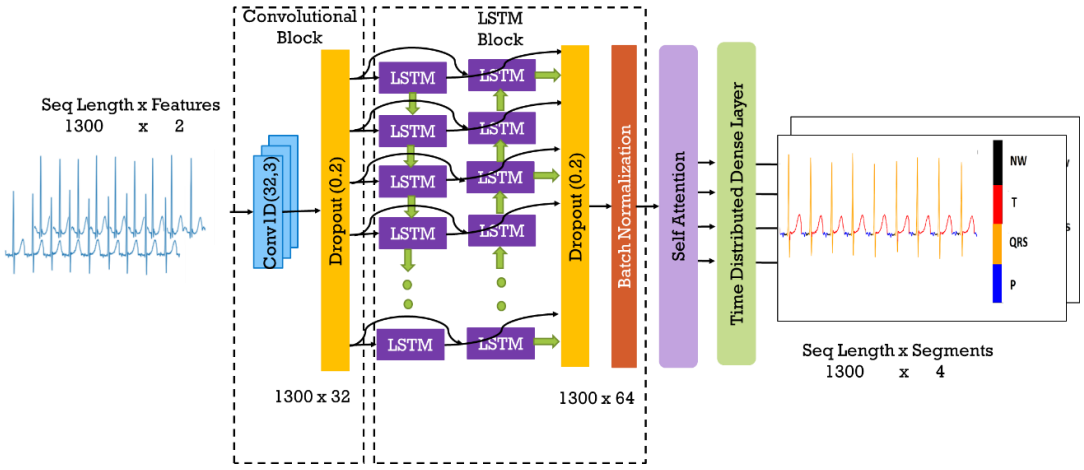

Figure 3. Conv-BiLSTM Architecture with Attention Mechanism for Segmenting the ECG Signal

After the development of automated ECG segmentation tool, the next step is to deploy them across different ECG datasets associated with different heart conditions. We aimed to classify among four heart conditions i.e., class labels are NSR, CHF, ARR and SCD. The class labelling was performed on the individual basis i.e. all the ECG beats corresponding to the patient were characterised as either NSR, CHF, ARR or SD. Each dataset has different sampling frequency. The ECG segmentation model was built upon dataset with the sampling frequency of 250Hz. Therefore, we up-sampled the NSR Database

(MIT-BIH Normal Sinus Rhythm Database [36]) from 128Hz to 250 Hz and down-sampled ARR database (MIT-BIH Arrhythmia Database [39]) from 360 Hz to 250 Hz. The sampling frequency of CHF (BIDMC Congestive Heart Failure Database [37]) and SCD (MIT-BIH Sudden Cardiac Death Holter database [38]) is 250 Hz. After deployment of ECG segmentation tool, we extracted 1-second ECG beats from the ECG signal with peak of QRS wave at half of the second (i.e. ECG beat centred at QRS peak) for training consistency in the next stage.

2.3 Stage 2: Automated CVD Detector

The second stage is towards CVD detector (Figure 4) based on time adaptive spectrogram driven multiclass deep learning architecture to detect different heart conditions. The term 'time adaptive' reflects the nature of the model, which can monitor the ECG signal where we can control the duration of the time ECG should be monitored in real-time settings. In contrast to previous approaches, which focus on extracting features from 1-D signal, our approach focuses on time-controlled ECG beats which are then converted into time-frequency based 2-D spectrogram. Previously, spectrogram has been used to represent the entire ECG signal into 2-D image. In contrast, our work focuses on representing individualized ECG beats extracted from the ECG signal into 2-D image. Moreover, the model does not rely on one heartbeat from each patient but sequence of individualized heart beats where duration depends on classification performance. This methodology would be quite helpful in detecting heart conditions in real time signals. We then deployed time adaptive deep learning architecture to perform multiclass classification.

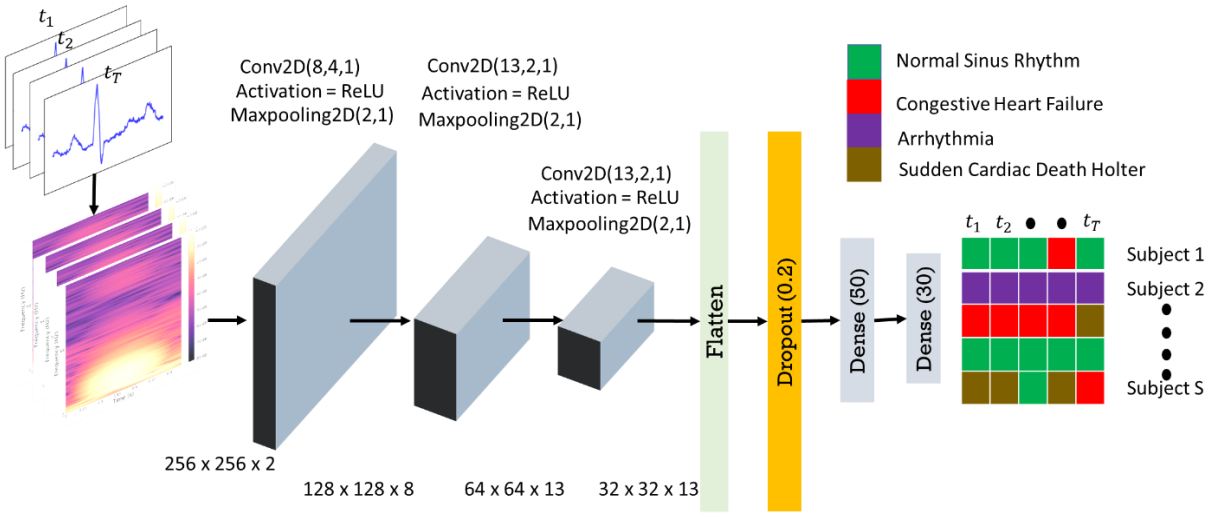

Figure 4. Multilayer Convolutional Neural Network Architecture for CVD Detector

2.3.1 ECG Spectrogram

The spectrogram is the representation of the signal strength at different frequencies with the time variation. There have been different techniques to represent the time-series signal into spectrogram. Under this context, we deployed Short Time Fourier Transform (STFT) [44]. The STFT is sequence of Fourier transforms of a signal across short overlapping windows, which provides time-localized signal strengths where frequency of the signal varies over time. The equation of STFT of the ECG beat is given as (eq. 4):

$$STFT\{x[k]\} = X_{STFT}[m,n] = \sum_{k=0}^{L-1} x[k]g[k-m]e^{-\frac{-j2\pi nk}{L}} \quad (4)$$

where $x[k]$ is the sequence of discretized ECG beat into time domain; whereas the $g[k-m]$ is the window function at time axis m; n is the frequency axis and L are total number of data points in $x[k]$. We also set 50% overlapping window with hop size equal to 1. Here we select *Hanning window* whose equation (eq. 5) is mentioned as follows:

$$g[m] = 0.5 - 0.5\cos(2\pi m/(M-1)) \quad 0 \le m \le M-1 \tag{5}$$

where M is the length of window function equal to 512. We finally obtained the X_{STFT} size equal to 256 x 256. We represented the spectrogram by converting the absolute value of X_{STFT} into decibel scale. The formula is as follows:

$$X_{STFT}^{db} = 20\,\log\_10[|X\_STFT\,|/\max(|X\_STFT\,|)] \tag{6}$$

We calculated the STFT for each ECG beat obtained from two-lead ECG signal, resulting in feature size equal to 256 x 256 x 2. The STFT spectrograms of the ECG beats from each of 4 classes are shown in Figure 5.

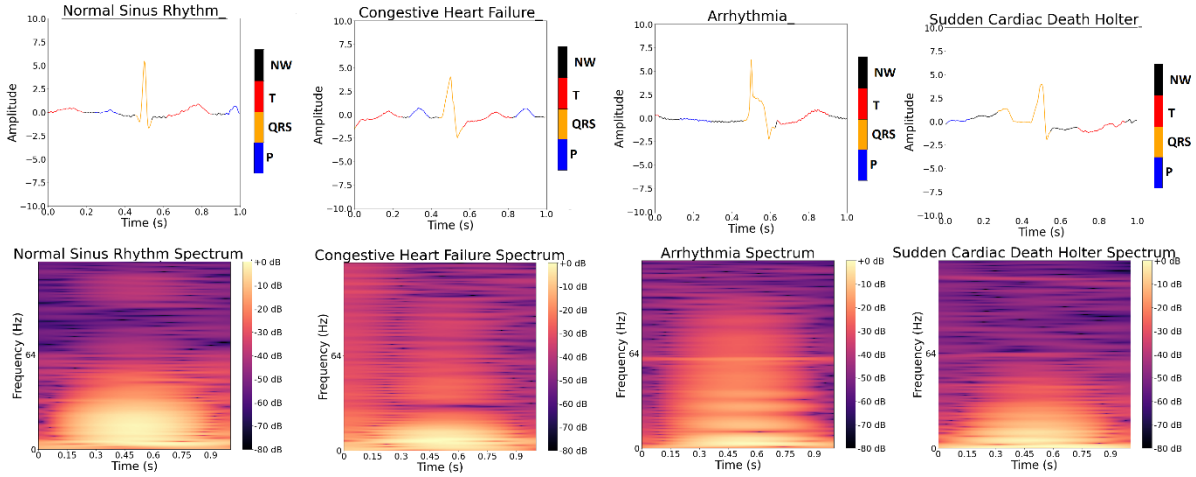

Figure 5. Spectrogram example of the ECG beats from each of the 4 classes

2.3.2 Multilayer Convolutional Neural Network

CNNs have been previously deployed as they are able to extract features from the image at the micro-level [45]. The layers in the CNN architecture are locally connected to extract and convolve the features by applying filter of certain kernel size. In contrast to RNN architectures, the CNN architectures are able to extract localized static information from the signal [46]. We developed and deployed a multilayer CNN architecture where the numbers of ECG beats extracted from each subject are adaptive to time control as shown in Figure 4.

We labeled each ECG beat of the subjects according to their respective heart conditions, resulting in ECG beats occurring from same subject at different times as different instances. Each instance is represented by 256 x 256 x 2 spectrogram obtained from two-lead ECG signal after STFT transformation input to three-layer 2D-CNN architecture. Each CNN layer is equipped by a ReLU activation function and Maxpooling layer; defined by following equations (eq. 7, 8, 9):

$$y_{2d} = W_{2d} \otimes x_{2d} + b \tag{7}$$

$$y_{2d_{act}} = ReLU(y_{2d}) \tag{8}$$

$$M_{x,y}(y_{2d_{act}}) = \max_{(a,b=0)^P} y_{2d_{act}}(Dx + a, Dy + b) \tag{9}$$

where, x is the input signal, $W$are 2-D convolutional weights, b the bias, $ReLU = \max(0, y)$ the activation function, $M_{x,y}$ the maxpooling with pooling size P and stride D.
In the first CNN layer, we have 8 filters with kernel size = 4 x 4, P = 2 x 2 and D = 1 x 1, resulting output of 128 x 128 x 8. The second and third layers have 13 filters with kernel size = 2 x 2, P = 2 x 2 and D = 1 x 1; resulting 32 x 32 x 13 (Figure 4). We then add 50% dropout to avoid overfitting followed by Dense Layer. The output of the architecture would be Tx S matrix where T is total number of ECG beats and S is total number of subjects. Each ECG beat is classified as either of NSR, CHF, ARR or SCD. The heart condition of the subject was determined by *majority voting scheme* which assigns the subject to heart condition based on majority of ECG beats being classified as either class within the specified time interval [28].

3 Training Protocol and Metrics

3.1 Multi class Classification Accuracy

The ECG segmentation and CVD detection/prediction accuracies evaluated across different heart conditions from PhysioNet's QT database. We have evaluated both accuracies according to the following formula (eq. 10):

$$Acc = (TP + TN)/(TP + TN + FP + FN) \tag{10}$$

where TP = number of data points correctly identified as part of individual ECG waves in stage 1 or heart condition correctly identified in stage 2; TN = number of data points correctly identified as not part of individual ECG waves or non-heart condition correctly identified in stage 2; whereas FP and FN are number of data points incorrectly identified in TP and TN , respectively.

3.2 Training and Testing

During the training and testing of the models in both ECG segmentation and CVD detection, we performed *subject-wise cross validation*. In subject-wise cross validation, the ECG sequences and beat extracts of the subjects used for training the model are not used to test even if they are not trained due to occurrence at different times. In both ECG segmentation and CVD detection, we performed 5-fold cross validation i.e. we divided the total number of subjects into 5 chunks, trained the model on ECG sequences and ECG beats of 4 chunks and tested on the same of 5th chunk.

3.3 Data Imbalance

After deployment of the ECG segmentation model, the number of ECG beats extracted for each time interval are shown in Table 1. This shows high data imbalance across different heart conditions as about half of the ECG beats belong to ARR. In order to avoid data imbalance problems the number of training instances from each heart condition were down-sampled to the size of SCD instances [47].

Table 1. Description of the Dataset used to train and test the CVD detector model.

CVD Detection Datasets	Sampling Frequency	Number of Patients	Total Number of ECG beats during each time interval							
			1 sec	10 sec	30 sec	1 min	2 min	3 min	4 min	5 min
NSR	128Hz	18	18	180	540	1080	2160	3240	4320	5400
CHF	250 Hz	15	15	150	450	900	1800	2700	3600	4500
SCD	250 Hz	12	12	120	360	720	1440	2160	2880	3600
ARR	360 Hz	48	48	480	1440	2880	5760	8640	11520	14400

NSR: Normal Sinus Rhythm; CHF: Congestive Heart Failure; ARR: Arrythmia; SCD: Sudden Cardiac Death

3.4 Experimental Setup

In both of ECG segmentation tool as well as CVD detector, we deployed AdamOptimizer function with the learning rate of 10^{-3} [48]. For stage 1, the batch size was set to 4 with epoch size = 200. During subject-wise multiclass cross validated classification, we trained the model on 80% of the subjects which has been tested on remaining 20% subjects. For stage 2, the batch size was set to 10 with epoch size equal to 20. We trained the model on 75% of the subjects, validated against 5% of the subjects and were tested on remaining 20% subjects. The models from both stages were developed on Quadro RTX 5000 GPU processor for improved computational time.

4 Results

4.1 ECG Segmentation Classification

The results of the ECG segmentation classification are presented in Supplementary Table 1. We performed subject-wise classification accuracy across 94 subjects obtained from QT database, which contains the ECG signals from different databases that collect patients with several types of heart conditions. The segmentation results were significantly accurate in terms of QRS segmentation (97%) across all databases compared to P wave (95%) and T wave (91%). We achieved an overall segmentation accuracy of 95%. Since we were concerned to centralize the ECG beat extract on QRS wave, we opted to locate the peak point of QRS with 0.5 seconds before and after peak point of QRS wave in order to extract a full ECG beat (after resampling NSR and ARR to 250Hz matching the sampling rate of CHF and SCD).

4.2 ECG beat Classification

After training and testing the ECG Segmentation tool on the QT database, we employed the model to extract ECG beats for NSR, CHF, ARR, and SCD signals. The results of automated CVD detector based on time adaptive ECG beats are shown in Supplementary Figure 1. The results in the confusion matrix show that during low time intervals, the most recurrent error was misleading CHF ECG beats with ARR beats, whereas SCD signal has been often classified as ARR. This may be expected as patients presenting with CHF and SCD are often initiated with a sustained arrhythmia. However, with the inclusion of more time interval, the ECG beat classification increased and stabilized across all four classes. We achieved the ECG classification accuracy of 95.93% by 5 minutes (Table 2).

Table 2. ECG beat classification accuracy (Percentage)

Heart Conditions	Time Intervals (Mean Accuracy ± Standard Deviation)							
	1 sec	10 sec	30 sec	1 min	2 min	3 min	4min	5 min
NSR (18 subjects)	88.9 ± 11.1	96.7 ± 4.9	99.8 ± 0.3	99.6 ± 1.0	99.9 ± 0.1	99.9 ± 0.06	99.9 ± 0.1	100 ± 0.0
CHF (15 subjects)	73.3 ± 24.9	92.7 ± 8.3	76.7 ± 14.8	90.6 ± 6.9	86.4 ± 8.5	92.2 ± 6.8	90.2 ± 3.7	94.2 + 5.2
ARR (48 subjects)	47.9 ± 15.7	83.1 ± 14.8	95.4 ± 3.2	93.9 ± 3.0	95.5 ± 3.6	93.7 ± 3.7	95.6 ± 3.4	95.1 ± 1.3
SCD (12 subjects)	75.0 ± 38.7	85.0 ± 13.0	77.2 ± 24.2	86.3 ± 10.1	94.9 ± 5.2	89.9 ± 7.6	87.7 ± 8.9	95.4 ± 3.2
Total (93 subjects)	63.2 ± 0.1	87.5 ± 0.1	90.9 ± 0.1	93.53 ± 0.0	94.8 ± 0.0	94.2 ± 0.0	94.5 ± 0.0	95.9 ± 0.0

NSR: Normal Sinus Rhythm; CHF: Congestive Heart Failure; ARR: Arrythmia; SCD: Sudden Cardiac Death

Figure 6 shows ECG beat classification across CHF, SCD and ARR within 5-minute time interval. We presented all examples of CHF and SCD however, we only selected 14 out of 48 examples from ARR which had highest number misclassified ECG beats. Figure 6 also shows the examples of the ECG beats along with their spectrogram for both correctly classified and misclassified ECG beats. By observing Supplementary Figure 1 and Figure 6, we note that ECG signal strength are often more concentrated in lower frequencies. CHF and ARR can be distinguished from NSR and SCD as they have comparatively stronger signals at frequencies above and below 64Hz. While comparison of CHF and ARR, CHF may have stronger signals at higher frequencies. However, ARR may also have strong high frequency

components, which can lead to ARR event detection in CHF and vice versa (subjects chf15, 232, 233). There are few high frequencies in the SCD beats, however, those which possess strong signals at high frequencies have detected ARR or CHF events. These is this because CHF and SCD patients presented some ARR events.

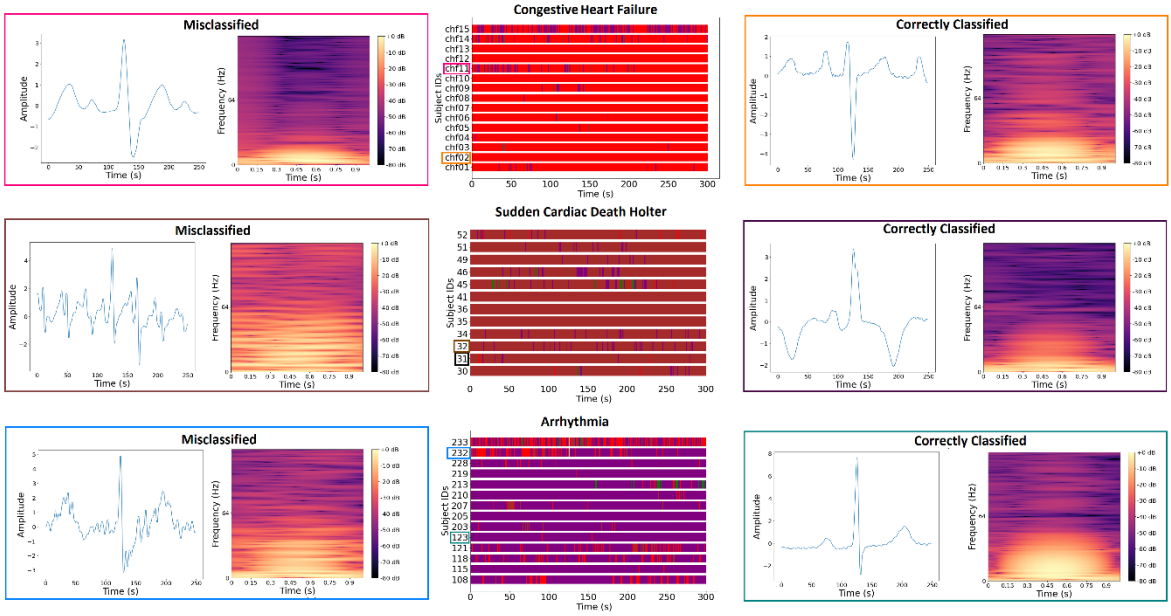

Figure 6. ECG beta classification for selected subjects of Congestive Heart Failure, Sudden Cardiac Death and Arrhythmia with spectrogram of correctly classified and misclassified ECG beats

4.3 CVD Detection based on Majority Voting

We performed CVD detection based on majority voting scheme i.e., the subject with majority of heart beats predicted to certain heart condition within certain time interval is assigned that heart condition. Table 3 shows the CVD detection accuracy across time intervals ranging from 1 second to 5 minutes. The results show that our CVD detector was able to outperform the existing state of the art methods within 4 minutes as we achieved 100 % accuracy for detecting events such as NSR, CHF and predict SCD whereas only one example of ARR (subject 233) was detected as CHF; making ARR detection accuracy as 97.91%. The model in the lower time intervals showed some inconsistency in terms of CHF detection and SCD prediction due to the limited number of ECG beats. However, the accuracy of the model can be improved for the lower time intervals as well by increasing the size of the training set.

Table 3. CVD detection accuracy across different time intervals

	Time Intervals							
Heart Conditions	**1 sec**	**10 sec**	**30 sec**	**1 min**	**2 min**	**3 min**	**4min**	**5 min**
NSR (18 subjects)	88.89%	100%	100%	100%	100%	100%	100%	100%
CHF (15 subjects)	73.33%	93.33%	73.33%	93.33%	86.67%	93.33%	100%	100%
ARR (48 subjects)	47.92%	83.33%	97.91%	97.91%	97.91%	97.91%	97.91%	97.91%
SCD (12 subjects)	75.00%	91.66%	83.33 %	91.66%	100%	100%	100%	100%
Total (93 subjects)	63.44%	89.24%	92.47%	96.77%	96.77%	97.84%	98.92%	98.92%

NSR: Normal Sinus Rhythm; CHF: Congestive Heart Failure; ARR: Arrythmia; SCD: Sudden Cardiac Death

As shown in Table 3, we observed that converting the1-D ECG signal into 2-D spectrogram can improve the classification performance of the CVD detection accuracy. Moreover, if we split the ECG signal into individualized ECG beats, we can also improve the classification performance for the limited time interval. Our detector outperforms the existing approaches and is able to limit the time interval with high detection accuracy across the 4 classes.

5 Discussion

In this study, we presented a complete tool via deep learning methods with the ability to automatically segment ECG beats using a ConvBiLSTM neural network with attention mechanism, followed by a second algorithm based on a time-adaptive CNN applied to ECG beats (10s, 30s, 1min, 2min, 3min, 4min and 5min) converted to 2D image via Short-Time Fourier Transform to automatically detect cardiac adverse events such as arrhythmia, congestive heart failure and predict sudden cardiac death. Our time adaptive ECG detector has outperformed most of the existing approaches with 95% ECG segmentation accuracy as well as 100% detection accuracy on CHF, NSR and SCD within 4 minutes of the ECG signal whereas only one subject out of 48 subjects affected by arrhythmia was detected as CHF, making arrhythmia detection accuracy as 97.91%. This could be due to presence of motion artefacts present in the ECG signals which may propagate due to presence of CHF or ARR events, resulting in high frequencies.

During the first stage of our tool, an automatic ECG segmentation was presented. Data containing 94 records from the QT database became the baseline for P-wave, QRS complex, and T-wave detection in the classification process. Using random sampling, we performed 5-fold subject wise cross-validated classification where in each fold, classification process was divided into 80% in the training phase and 20% in the test phase. We employed a Convolutional Bi-directional LSTM with attention mechanism, which acquire local features as well time variant features in both forward and backward direction along with contextual attention on time variant features. The model achieved an overall segmentation accuracy of 95%. Our approach outperformed existing approaches based on traditional machine learning features (such as Hidden Markov Model in wavelet encoding [49] managed to obtain 88%), BiLSTM based ECG-SegNet [18] obtaining the segmentation accuracy of 92% and ConvLSTM network deploying double layer of BiLSTM (94%) [50].

The main novelty of the model lies in detection and prediction of different heart conditions based on time adaptive spectrograms of the individual ECG beats extracted from the automated ECG segmentation model. Most of existing studies focus either on 1-D signal features or spectrogram of the entire ECG signal. In contrast to existing approaches, our approach focuses on 2-D spectrogram of the ECG beats obtained from the ECG segmentation tool, where time interval can be controlled to limit the ECG excerpt length. The second stage is based on multilayer 2D-CNN architecture, where the input of the signal is the individualized ECG beats extracted from the ECG signal of the subjects; whereas existing approaches focus on representing entire ECG signal into spectrogram [25]. Besides, the number of ECG beats can be controlled through time interval. We started the time interval from short-term benchmark (5 min) moving down to ultra-short-term time interval (1 sec). To obtain the image from the ECG signal, deployed spectrogram technique obtained via STFT, which represents the signal strength at different frequencies with time variation. Compared to other frequency analysis methods such as DWT and SWT, STFT results robust in terms of repeatability and robustness of the analysis and it is less expensive computationally as requires less coefficients than DWT and CWT [20]. The CVD detector based on CNN was able to classify NSR, CHF and ARR events, and predict SCD with an accuracy of 100%, 100%, 97.91% and 100% respectively in 4 min ECG window. According to the results obtained, the proposed method has classified the ECG signals belonging to ARR, CHF, SCD and NSR classes better than some existing algorithms from MIT-BIH database, considering that the proposed method is able to predict SCD simultaneously with cardiac events detection in different time windows. The performance of the model across different time window are kept quite constant. A drop of overall accuracy is shown when moving from 5 min to ultra-short time windows. This could be mainly due to the use of a smaller number of ECG beats used to train and validate the model. Besides, the spectrogram of both ARR and CHF may have high frequency components, which may have also resulted in the misclassification of CHF ECG beats as ARR and vice versa. Probably, this is due to ARR events presented in the CHF or SCD patients. However, the increase in number of subjects could result in high CVD detection accuracy within lower time interval.

Several studies have attempted to classify automatically CVD by using traditional and more advanced artificial intelligence techniques [28, 51, 52]. Studies that have employed the same datasets adopted not more

than 2 different classes (Table 4). Only one study [25] adopted a multilabel classification by using MIT-ARR Database, BIDMB Congestive Heart Failure and MIT-BIH Normal Sinus Rhythm. They achieved an overall accuracy of 96.77%, 96.77 and 100% for ARR, CHF and NSR respectively, by using around 10 min window ECGs. Our model not only outperformed the accuracy achieved in [25] but it was also based on 4 class classification as well as within limited time interval i.e. 4 minutes. The model used by Cinar et al. [25] for multiclass classification was Alexnet-SVM, whereas we proposed simpler multilayer CNN for multiclass CVD detection based on majority voting scheme. Unlike the existing literature, ARR, CHF, NSR, and SCD ECG signals were evaluated together in the presented study. Another work by Daqrouq and Dobaie (2016) [22], attempted to classify ARR, CHF, and NSR. They used a wavelet transform of 12 beats and input ECG features in a classification method by three confirmation functions. However, they trained multiple binary classifiers by reporting performance of ARR vs NSR and CHF vs NSR.

Several studies have investigated CHF versus Normal Sinus Rhythm via deep learning methods achieving good performance. Porumb et al. [28] used 5 min ECG heartbeats to automatically detect CHF by using a CNN based method. They achieved an overall accuracy of 97.8% in ECG beat classification within 5-minute interval while being compared with NSR only. Whereas we achieved comparable 94.2% accuracy and this drop in performance may be explained by the fact that the spectrogram of the CHF ECG beat can be often confused with ARR ECG beat due to presence of high frequency components and, therefore, can be misclassified in presence of NSR and SCD. Other studies [23, 29] also performed binary classification to automatically detect CHF versus NSR by using longer time frame ECG and highly pre-processed ECG achieving around 99% accuracy. Compared to our results, they yet used a binary classification and a more complex architecture while we employed comparatively shallow architecture (i.e., with 3 convolutional layers with small filter numbers and kernel size).

Some studies also investigated MIT-BIH arrhythmia against Normal Sinus Rhythm. Our methods outperformed most of these studies [3, 30, 31, 53] by showing a higher accuracy in a multiclass classification problem. Most of these studies employed 1-D CNN with more than 3 layers.

Lastly, sudden cardiac death has also been investigated in several studies, that are different in research contexts, research objectives, datasets, used variables and validation procedures, making the comparison of studies challenging with our model. The most frequently observed research objective was the classification of SCD and non-SCD via traditional machine learning [54] and by using Heart Rate Variability features as predictors [55, 56]. One recent study, Kaspal et al. [57], used a CNN combined with a Recurrence Complex Network (RCN) to enhance the accuracy of SCD classification. The recurrence matrix from the RCN will generate Eigen values and then, CNN will extract features and detect SCD by analyzing the Eigen values. They were able to detect MIT-BIH SCD patients with an accuracy of 90.60%, whereas we achieved 100% from 2 to 5 min ECG windows.

Overall, although ECG-based diagnostic models have so far focused only on single-type predictions, our analysis shows that AI is capable of multi-type CVD diagnosis by achieving good results also in small time frame ECG windows.

5.1 Limitations and Future works

However, this study presents some limitations. Because of the retrospective nature of the data collection, the publicly available datasets used in this study presented some missing information and limitations. CHF, atrial fibrillation and ventricular arrhythmia and sudden cardiac death may overlap in the same patient. Therefore, in some patients these conditions were not mutually exclusive. Moreover, we did not investigate the different number of arrhythmia (e.g. roughly six classes) presented in the used dataset. Atrial and ventricular arrhythmia may lead to different results because there is a great day-to-variation in ventricular as well in atrial arrhythmias. Moreover, they may be both present in the same patient eventually with CHF or aborted sudden death. This point will be further analysed in the next studies. Regarding the patients that suffered SCD, it is unclear if these patients died during the index Holter and which type of sudden death was documented. In fact, patient information was limited, and some cases may not be representative of

spontaneous episodes of sudden death. Beside these shortcomings, these recordings may provide important evidence to the pathogenesis of sudden death syndrome. In further studies, we will also investigate among CHF patients those at high risk of sudden death that may require an implantable cardioverter-defibrillator.

Moreover, for smaller amount of training data, the 2D-CNN architecture methods could face overfitting problems since the model highly pay attention to training data and do not generalize well for the test data. Thus, we used shallow techniques to provide better performance on small amount of data samples. Secondly, increasing the time interval for ECG beat extraction and their 2D spectrograms require huge amount of memory. In order to provide the real-time CVD detection for limited time, we require higher amount of subject size.

Additionally, repeated under sampling method could have affected the accuracy of the model. We have down sampled twice i.e. firstly, to match the sampling frequency of the ECG signals from different patients to the sampling frequency of the ECG segmentation i.e. 250Hz as keeping the original sampling rate from each class may affect the ECG segmentation performance. In fact, the sampling frequency has to be consistent otherwise it would introduce sampling bias in the classification process. Secondly, the down sampling was performed to address the data imbalance to match the number of instances of the lowest class for the improved classification accuracy. However, this can be assessed in future works, where specific study protocols can be designed aiming at answering this specific aspect.

The future work of this research study is to use more optimization techniques, simpler classification algorithms to improve the performance of the predictive system for the diagnosis of heart diseases. Moreover, this work can be extended by training a larger dataset, particularly on more cardiac abnormalities. Further studies will also investigate other important characteristics such as patients' physical state (e.g., age, gender, physical conditions, lifestyle, etc) in the CVD detector tool.

Although our system is quite far for a commercial use as it needs further validation, clinical studies, and appropriate certifications, we could anticipate that the proposed system will be useful and helpful for the physician to diagnose heart disease accurately and effectively in real-life scenario. The system was built for two-lead ECG signals with a sampling frequency of 250Hz. No specific ECG device is needed, a resolution of 12 bits is preferred. The ECG can be obtained by placing the electrodes on the chest as it is standard practice for ambulatory ECG recording. Moreover, the subjects can carry on their usual life with no restriction, as the main aim of our system is to being able to detect and predict in real time CVD.

Table 1. CVD Detector Accuracy compared to State-of-the-Art

Author, year	Methods	Dataset	Results (ACC)
BIDMB CHF			
Darmawahyuni et al. (2020) [23]	Pre-processed 15 min ECG; LSTM based methods	1. MIT-BIH Normal Sinus Rhythm Database 2. BIDMB Congestive Heart Failure	99.86%
Porumb et al. (2020) [28]	5 min ECG; CNN based method	1. MIT-BIH Normal Sinus Rhythm Database 2. BIDMB Congestive Heart Failure	97.8 %
Zhang et al. (2020) [29]	Pre-processed ECG, 500 points (369.5s); Densely connected deep network-based method	33 CHF patients from 6 databases and 58 healthy subjects (control group) from 2 databases. 1. Long-Term ST Database 2. MGH/MF Waveform Database 3. Sudden Cardiac Death Holter Database 4. Cerebral Vasoregulation in Elderly with Stroke Database 5. BIDMC Congestive Heart Failure Database 6. PTB Diagnostic ECG Database 7. Fantasia 8. MIT-BIH Normal Sinus Rhythm Database	99.02%
MIT-BIH arrhythmia			
Avanzato et al. (2020) [3]	30s segments ECG; 1-D CNN, 5-layer	1.MIT- BIH Normal sinus rhythm database. 2.MIT-BIH arrhythmia	98.33%
Savalia et al. (2018) [30]	Pre-processed 10s ECG; ECG features extraction; 1-D CNN, 5-layer	1. MIT- BIH Normal sinus rhythm database. 2. MIT-BIH arrhythmia 3. Keggar	88%

Li et al. (2017) [53]	pre-processed ECG; 201 sampling points (148.74s); Wavelet transform; 1-D CNN, 6-layer	1.MIT- BIH Normal sinus rhythm database. 2.MIT-BIH arrhythmia	97%
Zubair et al. (2016) [31]	30 min ECG; 1-D CNN; 4-layer	1.MIT- BIH Normal sinus rhythm database. 2.MIT-BIH arrhythmia	92%
Sudden cardiac Death			
Kaspal et al. (2020) [57]	ECG features extraction; CNN	1. Sudden Cardiac Death Holter Database. 2. MIT-BIH Arrhythmia	90.60% 93.24%
Devi et al. (2019) [58]	pre-processed 5min ECG; Feature extraction (HRV: time domain, frequency domain, non- linear); SVM, KNN, Tree	1. Sudden Cardiac Death Holter Database. 2. Normal Sinus Rhythm databases.	83%
Fairooz et al. (2016) [54]	pre-processed 30min ECG; ECG features extraction; SVM	1. Sudden Cardiac Death Holter Database.	100%
CHF and Arrythmia			
Cinar et al. (2020) [25]	raw windows of 771 values ECG signals were converted into spectrogram images; Alexnet-SVM based method	1. MIT-ARR Database 2. BIDMB Congestive Heart Failure. 3. MIT-BIH Normal Sinus Rhythm	AR: 96.77% CHF: 96.77% NSR: 100%
Daqrouq and Dobaie (2016) [22]	Wavelet Packet Transform of 12 beats; ECG features extraction; classification method by three confirmation functions	1. MIT-BIH Normal Sinus Rhythm Database 2. BIDMB Congestive Heart Failure. 3. MIT-ARR Database	CHF with NSR: 92.6%. CHF with ARR: 86.67%
CHF, Arrythmia and Sudden Cardiac Death			
Proposed Method	10s, 30s, 1 to 5 min ECGs; STFT transformation; CNN	1. MIT-BIH Normal Sinus Rhythm 2. BIDMB Congestive Heart Failure 3.MIT-ARR Database 4.Sudden Cardiac Death Holter Database.	**From 4 min:** **100%,** **100%,** **97.91%,** **100%**

6 Conclusion

The study presented a novel and highly effective tool for CVD detection based on deep learning methods. The added value of our tool is that it uses raw ECG signals, rather than features, and achieve high accuracy in detecting arrhythmia, congestive heart failure and sudden cardiac death also in ultra-short time ECG windows. Moreover, to the best of the authors knowledge, this is the first study using advanced machine learning approaches to evaluate together several adverse cardiac events via ECG signals. Our CVD detector outperformed most of the state-of-the art-approaches with 100% detection accuracy of normal sinus rhythm, congestive heart failure and sudden cardiac death and 97.91% for arrhythmia within 4 minutes of the ECG signal. The achieved results help to reduce domain experts work, by computing useful signal characteristics via an automated complete system for early diagnosis of CVD. Due to its time adaptive nature, this tool has the capability to be implemented under real-time settings for early detection of different heart conditions and to be tested for prognostic risk stratification in patients with known heart disease.

Declaration of Competing Interest

The authors report no declarations of interest.

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References

1. Alfaras, M., M.C. Soriano, and S. Ortín, *A fast machine learning model for ECG-based heartbeat classification and arrhythmia detection.* Frontiers in Physics, 2019. **7**: p. 103.
2. Li, D., Y. Tao, J. Zhao, and H. Wu, *Classification of Congestive Heart Failure from ECG Segments with a Multi-Scale Residual Network.* Symmetry, 2020. **12**(12): p. 2019.

3. Avanzato, R. and F. Beritelli, *Automatic ECG diagnosis using convolutional neural network.* Electronics, 2020. **9**(6): p. 951.
4. Rubart, M. and D.P. Zipes, *Mechanisms of sudden cardiac death.* The Journal of clinical investigation, 2005. **115**(9): p. 2305-2315.
5. Barletta, V., I. Fabiani, C. Lorenzo, I. Nicastro, and V. Di Bello, *Sudden cardiac death: A review focused on cardiovascular imaging.* Journal of cardiovascular echography, 2014. **24**(2): p. 41.
6. Galli, A., F. Ambrosini, and F. Lombardi, *Holter monitoring and loop recorders: from research to clinical practice.* Arrhythmia & electrophysiology review, 2016. **5**(2): p. 136.
7. Schwalm, J.-D., M. McKee, M.D. Huffman, and S. Yusuf, *Resource effective strategies to prevent and treat cardiovascular disease.* Circulation, 2016. **133**(8): p. 742-755.
8. Lyon, A., A. Mincholé, J.P. Martínez, P. Laguna, and B. Rodriguez, *Computational techniques for ECG analysis and interpretation in light of their contribution to medical advances.* Journal of The Royal Society Interface, 2018. **15**(138): p. 20170821.
9. Zeadally, S., F. Siddiqui, Z. Baig, and A. Ibrahim, *Smart healthcare: Challenges and potential solutions using internet of things (IoT) and big data analytics.* PSU research review, 2019.
10. Belle, A., R. Thiagarajan, S. Soroushmehr, F. Navidi, D.A. Beard, and K. Najarian, *Big data analytics in healthcare.* BioMed research international, 2015. **2015**.
11. De Falco, I., G. De Pietro, G. Sannino, U. Scafuri, E. Tarantino, A. Della Cioppa, and G.A. Trunfio. *Deep neural network hyper-parameter setting for classification of obstructive sleep apnea episodes*. in *2018 IEEE Symposium on Computers and Communications (ISCC)*. 2018. IEEE.
12. Houssein, E.H., M. Kilany, and A.E. Hassanien, *ECG signals classification: a review.* International Journal of Intelligent Engineering Informatics, 2017. **5**(4): p. 376-396.
13. Moskalenko, V., N. Zolotykh, and G. Osipov. *Deep learning for ECG segmentation*. in *International conference on neuroinformatics*. 2019. Springer.
14. Xiang, Y., Z. Lin, and J. Meng, *Automatic QRS complex detection using two-level convolutional neural network.* Biomedical engineering online, 2018. **17**(1): p. 1-17.
15. Beraza, I. and I. Romero, *Comparative study of algorithms for ECG segmentation.* Biomedical Signal Processing and Control, 2017. **34**: p. 166-173.
16. Abrishami, H., M. Campbell, C. Han, R. Czosek, and X. Zhou. *P-QRS-T localization in ECG using deep learning*. in *2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)*. 2018. IEEE.
17. Xie, L., Z. Li, Y. Zhou, Y. He, and J. Zhu, *Computational Diagnostic Techniques for Electrocardiogram Signal Analysis.* Sensors, 2020. **20**(21): p. 6318.
18. Abrishami, H., C. Han, X. Zhou, M. Campbell, and R. Czosek. *Supervised ecg interval segmentation using lstm neural network*. in *Proceedings of the International Conference on Bioinformatics & Computational Biology (BIOCOMP)*. 2018. The Steering Committee of The World Congress in Computer Science, Computer ….
19. Byeon, Y.-H., S.-B. Pan, and K.-C. Kwak, *Intelligent deep models based on scalograms of electrocardiogram signals for biometrics.* Sensors, 2019. **19**(4): p. 935.
20. Addison, P.S., *Wavelet transforms and the ECG: a review.* Physiological measurement, 2005. **26**(5): p. R155.
21. Gothwal, H., S. Kedawat, and R. Kumar, *Cardiac arrhythmias detection in an ECG beat signal using fast fourier transform and artificial neural network.* Journal of Biomedical Science and Engineering, 2011. **4**(04): p. 289.
22. Daqrouq, K. and A. Dobaie, *Wavelet based method for congestive heart failure recognition by three confirmation functions.* Computational and mathematical methods in medicine, 2016. **2016**.
23. Darmawahyuni, A., S. Nurmaini, M. Yuwandini, M.N. Rachmatullah, F. Firdaus, and B. Tutuko, *Congestive heart failure waveform classification based on short time-step analysis with recurrent network.* Informatics in Medicine Unlocked, 2020. **21**: p. 100441.
24. Ebrahimi, Z., M. Loni, M. Daneshtalab, and A. Gharehbaghi, *A review on deep learning methods for ECG arrhythmia classification.* Expert Systems with Applications: X, 2020: p. 100033.
25. Çınar, A. and S.A. Tuncer, *Classification of normal sinus rhythm, abnormal arrhythmia and congestive heart failure ECG signals using LSTM and hybrid CNN-SVM deep neural networks.* Computer Methods in Biomechanics and Biomedical Engineering, 2020: p. 1-12.

26. Jahmunah, V., S.L. Oh, J.K.E. Wei, E.J. Ciaccio, K. Chua, T.R. San, and U.R. Acharya, *Computer-aided diagnosis of congestive heart failure using ecg signals–a review.* Physica Medica, 2019. **62**: p. 95-104.
27. Acharya, U.R., H. Fujita, S.L. Oh, Y. Hagiwara, J.H. Tan, M. Adam, and R. San Tan, *Deep convolutional neural network for the automated diagnosis of congestive heart failure using ECG signals.* Applied Intelligence, 2019. **49**(1): p. 16-27.
28. Porumb, M., E. Iadanza, S. Massaro, and L. Pecchia, *A convolutional neural network approach to detect congestive heart failure.* Biomedical Signal Processing and Control, 2020. **55**: p. 101597.
29. Zhang, Y. and M. Xia. *Application of deep neural network for congestive heart failure detection using ECG signals*. in *Journal of Physics: Conference Series*. 2020. IOP Publishing.
30. Savalia, S. and V. Emamian, *Cardiac arrhythmia classification by multi-layer perceptron and convolution neural networks.* Bioengineering, 2018. **5**(2): p. 35.
31. Zubair, M., J. Kim, and C. Yoon. *An automated ECG beat classification system using convolutional neural networks*. in *2016 6th international conference on IT convergence and security (ICITCS)*. 2016. IEEE.
32. Somani, S., A.J. Russak, F. Richter, S. Zhao, A. Vaid, F. Chaudhry, J.K. De Freitas, N. Naik, R. Miotto, and G.N. Nadkarni, *Deep learning and the electrocardiogram: review of the current state-of-the-art.* EP Europace, 2021.
33. De Falco, I., G. De Pietro, A. Della Cioppa, G. Sannino, U. Scafuri, and E. Tarantino, *Evolution-based configuration optimization of a Deep Neural Network for the classification of Obstructive Sleep Apnea episodes.* Future Generation Computer Systems, 2019. **98**: p. 377-391.
34. Sannino, G. and G. De Pietro, *A deep learning approach for ECG-based heartbeat classification for arrhythmia detection.* Future Generation Computer Systems, 2018. **86**: p. 446-455.
35. Laguna, P., R.G. Mark, A. Goldberg, and G.B. Moody. *A database for evaluation of algorithms for measurement of QT and other waveform intervals in the ECG*. in *Computers in cardiology 1997*. 1997. IEEE.
36. Goldberger, A.L., L.A. Amaral, L. Glass, J.M. Hausdorff, P.C. Ivanov, R.G. Mark, J.E. Mietus, G.B. Moody, C.-K. Peng, and H.E. Stanley, *PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals.* circulation, 2000. **101**(23): p. e215-e220.
37. Baim, D.S., W.S. Colucci, E.S. Monrad, H.S. Smith, R.F. Wright, A. Lanoue, D.F. Gauthier, B.J. Ransil, W. Grossman, and E. Braunwald, *Survival of patients with severe congestive heart failure treated with oral milrinone.* Journal of the American College of Cardiology, 1986. **7**(3): p. 661-670.
38. Greenwald, S.D., *The development and analysis of a ventricular fibrillation detector*. 1986, Massachusetts Institute of Technology.
39. Moody, G.B. and R.G. Mark, *The impact of the MIT-BIH arrhythmia database.* IEEE Engineering in Medicine and Biology Magazine, 2001. **20**(3): p. 45-50.
40. Blanco-Velasco, M., B. Weng, and K.E. Barner, *ECG signal denoising and baseline wander correction based on the empirical mode decomposition.* Computers in biology and medicine, 2008. **38**(1): p. 1-13.
41. Tikkanen, P., *Nonlinear wavelet and wavelet packet denoising of electrocardiogram signal.* Biological cybernetics, 1999. **80**(4): p. 259-267.
42. Medsker, L.R. and L. Jain, *Recurrent neural networks.* Design and Applications, 2001. **5**.
43. Hochreiter, S. and J. Schmidhuber, *Long short-term memory.* Neural computation, 1997. **9**(8): p. 1735-1780.
44. Nasser, K., *Digital Signal Processing System Design: LabVIEW Based Hybrid Programming*. 2008, San Diego: Elsevier.
45. Li, Q., W. Cai, X. Wang, Y. Zhou, D.D. Feng, and M. Chen. *Medical image classification with convolutional neural network*. in *2014 13th international conference on control automation robotics & vision (ICARCV)*. 2014. IEEE.
46. Liang, G., H. Hong, W. Xie, and L. Zheng, *Combining convolutional neural network with recursive neural network for blood cell image classification.* IEEE Access, 2018. **6**: p. 36188-36197.
47. Xu, S.S., M.-W. Mak, and C.-C. Cheung, *Towards end-to-end ECG classification with raw signal extraction and deep neural networks.* IEEE journal of biomedical and health informatics, 2018. **23**(4): p. 1574-1584.

48. Kingma, D.P. and J. Ba, *Adam: A method for stochastic optimization.* arXiv preprint arXiv:1412.6980, 2014.
49. Hughes, N., L. Tarassenko, and S.J. Roberts, *Markov models for automated ECG interval analysis.* Advances in Neural Information Processing Systems, 2003. **16**: p. 611-618.
50. Malali, A., S. Hiriyannaiah, G. Siddesh, K. Srinivasa, and N. Sanjay, *Supervised ECG wave segmentation using convolutional LSTM.* ICT Express, 2020. **6**(3): p. 166-169.
51. Hussain, L., I.A. Awan, W. Aziz, S. Saeed, A. Ali, F. Zeeshan, and K.S. Kwak, *Detecting congestive heart failure by extracting multimodal features and employing machine learning techniques.* BioMed research international, 2020. **2020**.
52. Raj, S., K.C. Ray, and O. Shankar, *Cardiac arrhythmia beat classification using DOST and PSO tuned SVM.* Computer methods and programs in biomedicine, 2016. **136**: p. 163-177.
53. Li, D., J. Zhang, Q. Zhang, and X. Wei. *Classification of ECG signals based on 1D convolution neural network*. in *2017 IEEE 19th International Conference on e-Health Networking, Applications and Services (Healthcom)*. 2017. IEEE.
54. Fairooz, T. and H. Khammari, *SVM classification of CWT signal features for predicting sudden cardiac death.* Biomedical Physics & Engineering Express, 2016. **2**(2): p. 025006.
55. Javan, S.L., M.M. Sepehri, and H. Aghajani, *Toward analyzing and synthesizing previous research in early prediction of cardiac arrest using machine learning based on a multi-layered integrative framework.* Journal of biomedical informatics, 2018. **88**: p. 70-89.
56. Devi, R., H.K. Tyagi, and D. Kumar, *Heart rate variability analysis for early stage prediction of sudden cardiac death.* International Journal of Electrical and Computer Engineering, 2016. **10**(3): p. 432-435.
57. Kaspal, R., A. Alsadoon, P. Prasad, N.A. Al-Saiyd, T.Q.V. Nguyen, and D.T.H. Pham, *A novel approach for early prediction of sudden cardiac death (SCD) using hybrid deep learning.* Multimedia Tools and Applications, 2021. **80**(5): p. 8063-8090.
58. Devi, R., H.K. Tyagi, and D. Kumar, *A novel multi-class approach for early-stage prediction of sudden cardiac death.* Biocybernetics and Biomedical Engineering, 2019. **39**(3): p. 586-598.

Figure 1

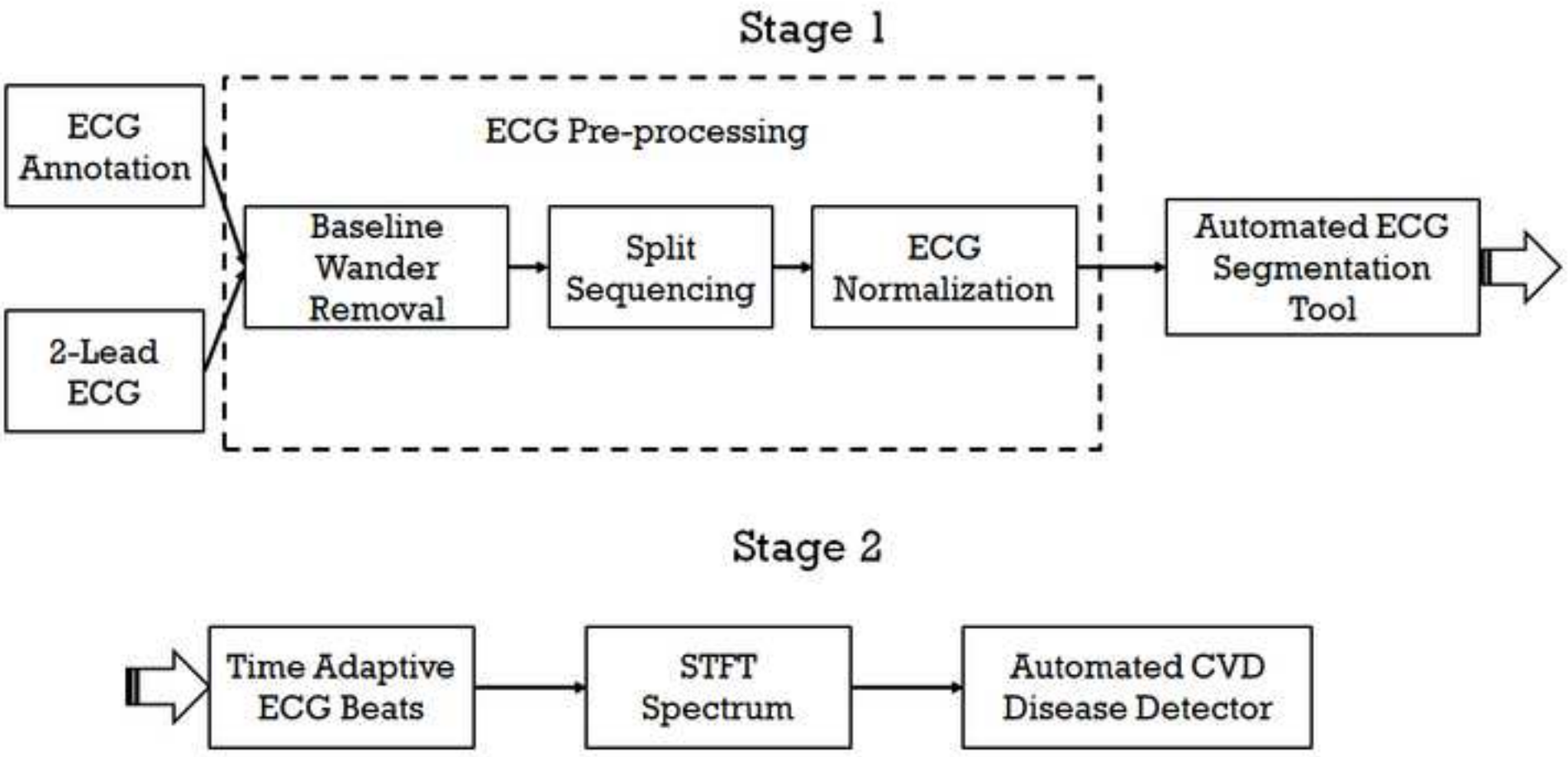
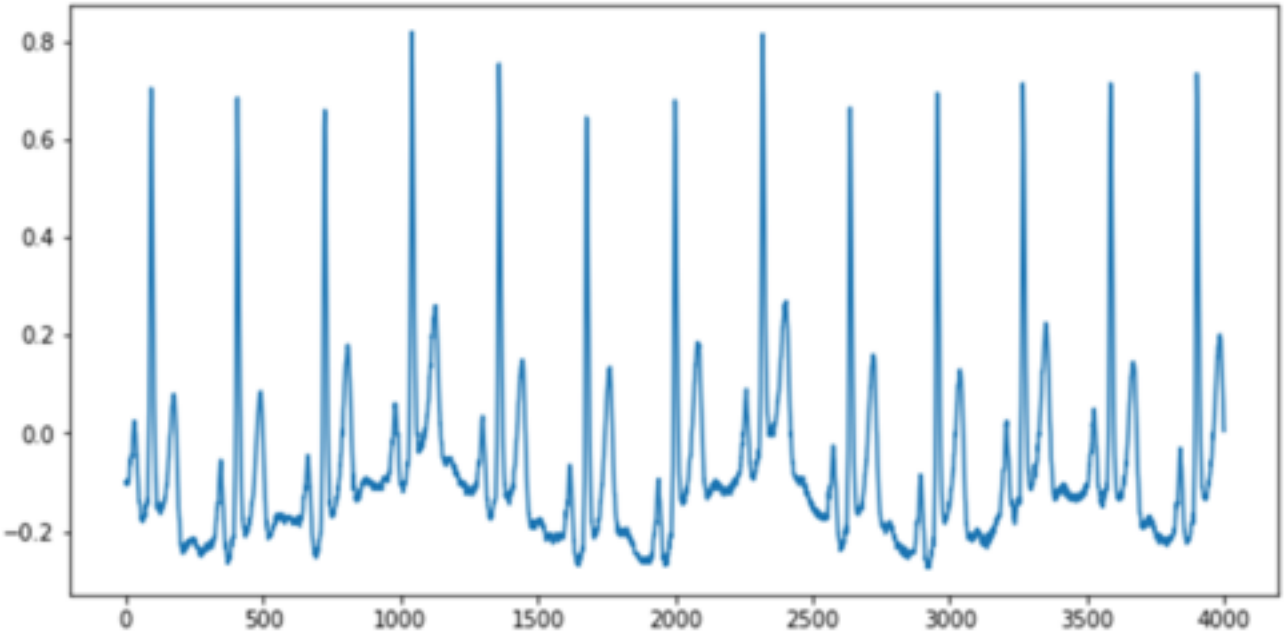
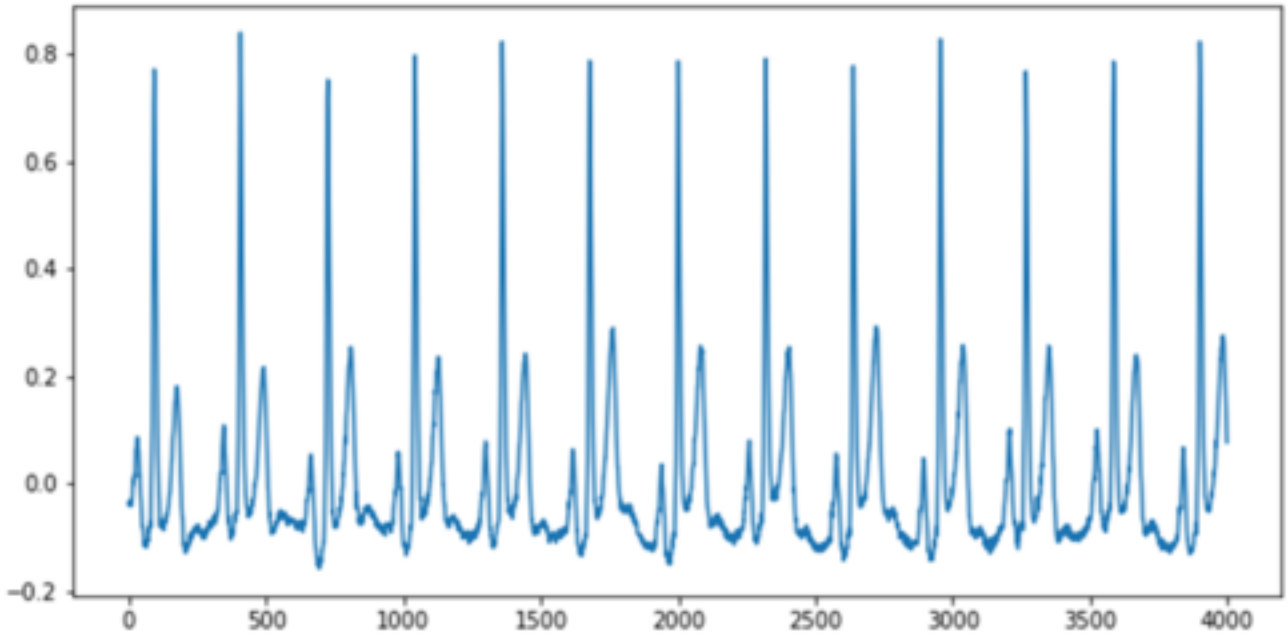


Figure 2



(a)



(b)

Figure 3

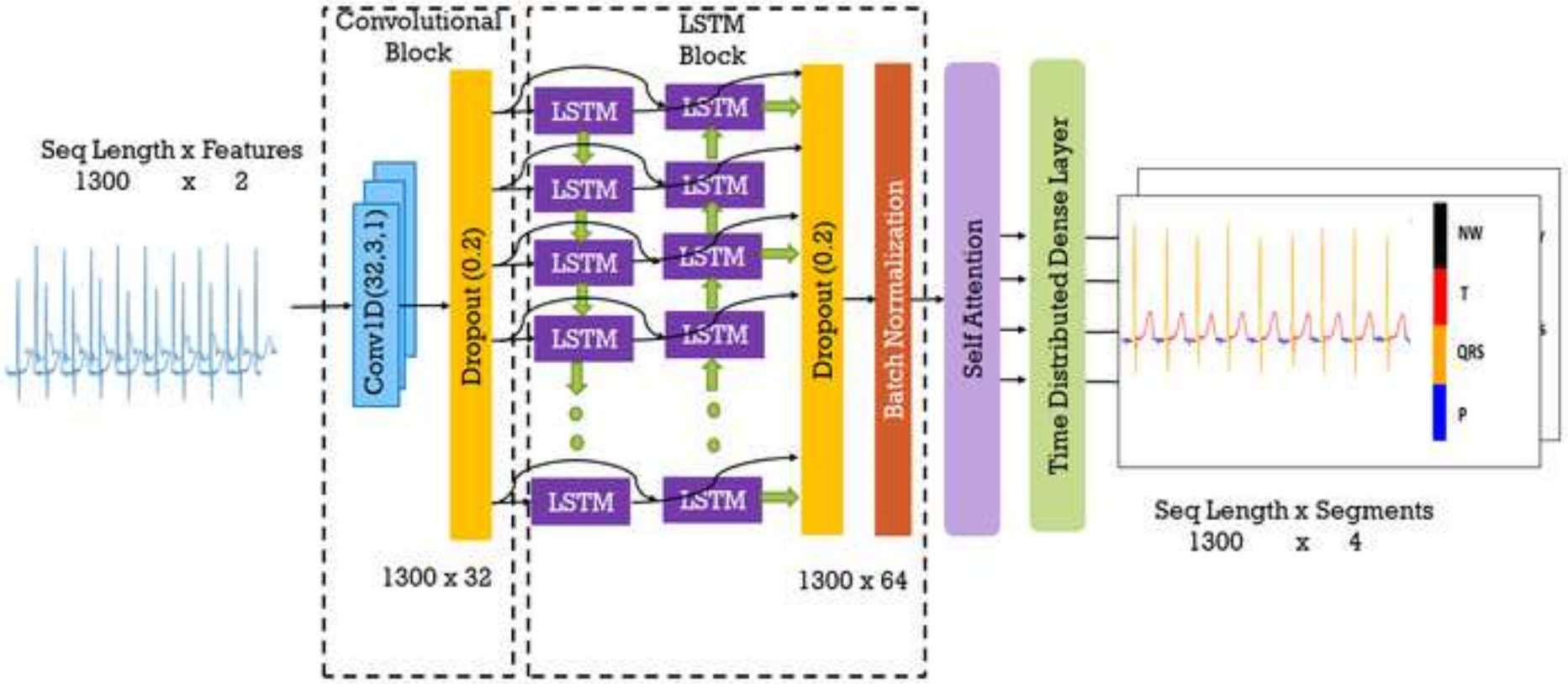


Figure 4

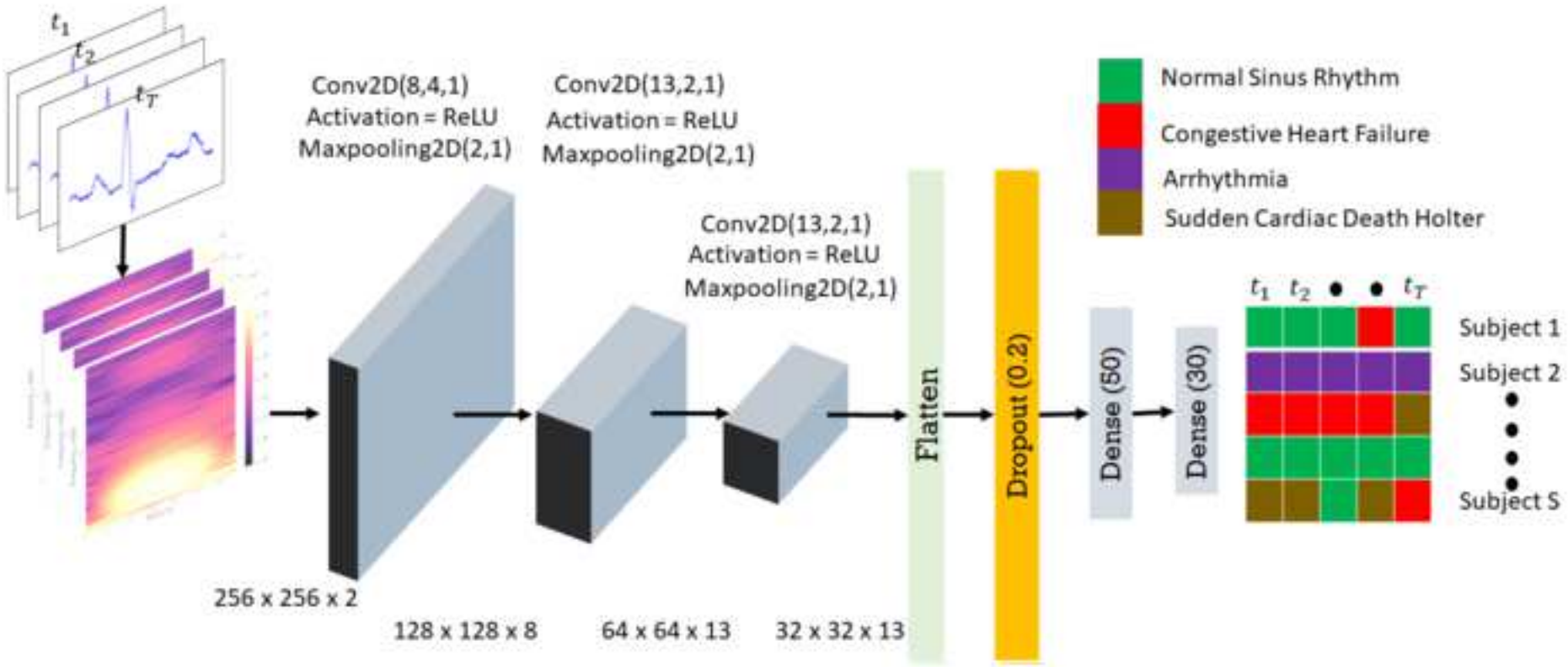


Figure 5

Click here to access/download;Figure;Figure5_300.tif

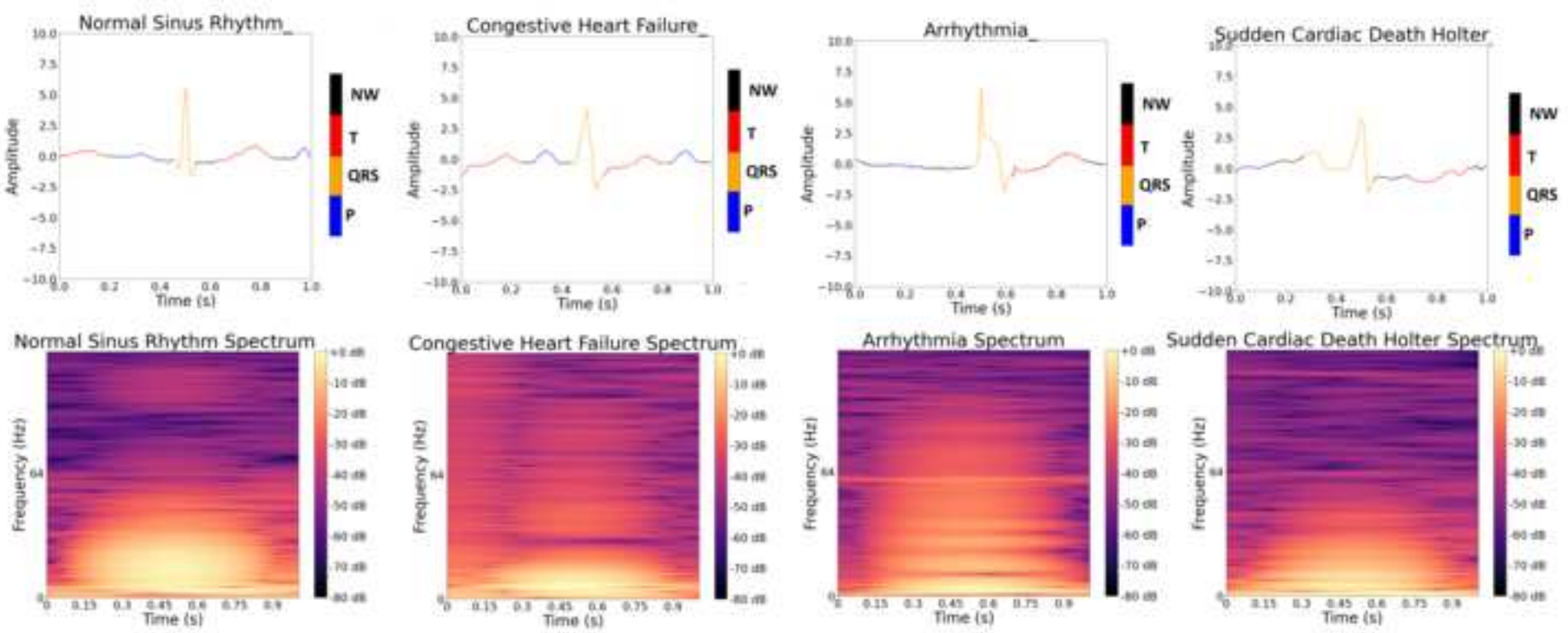
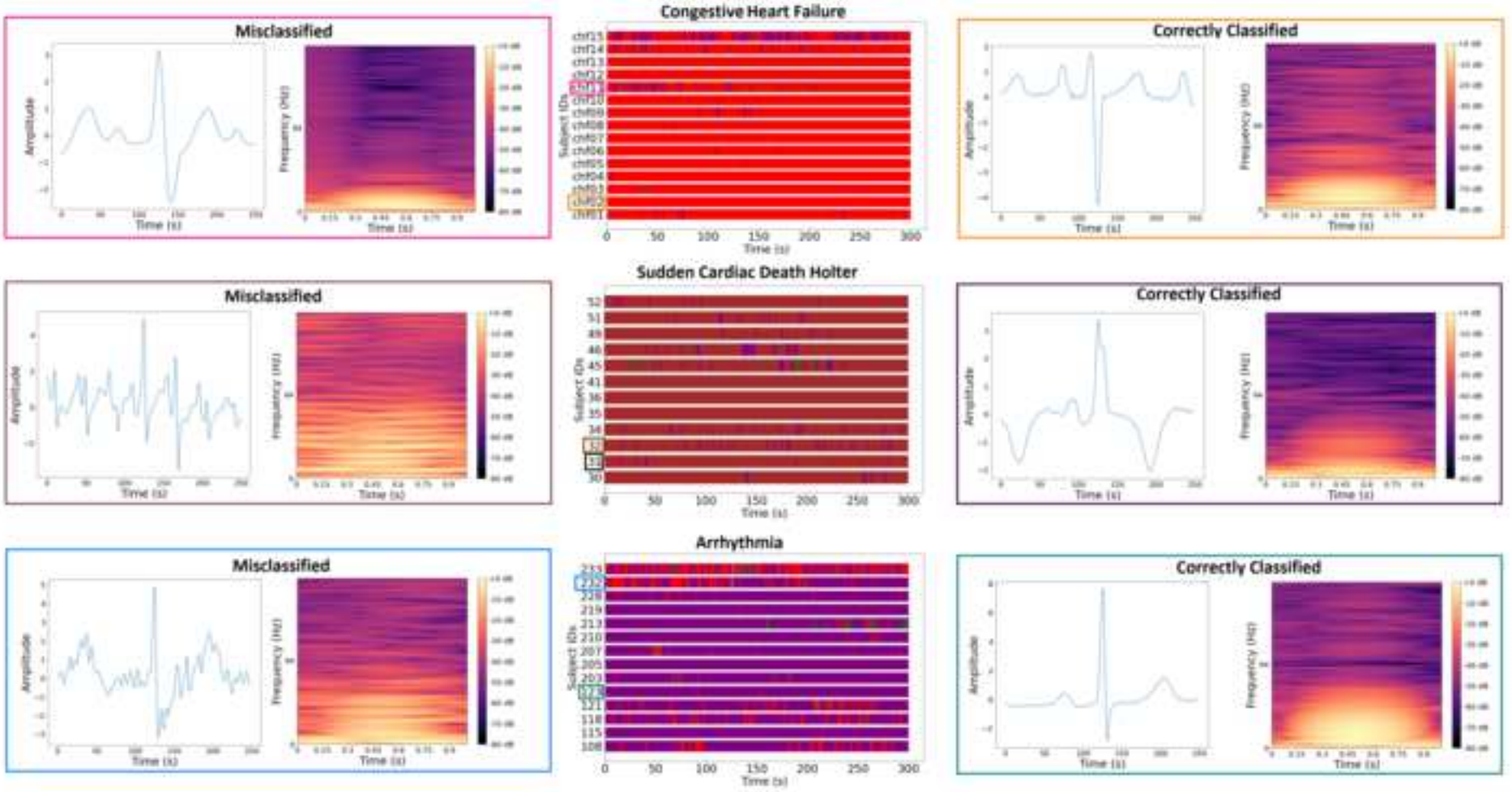
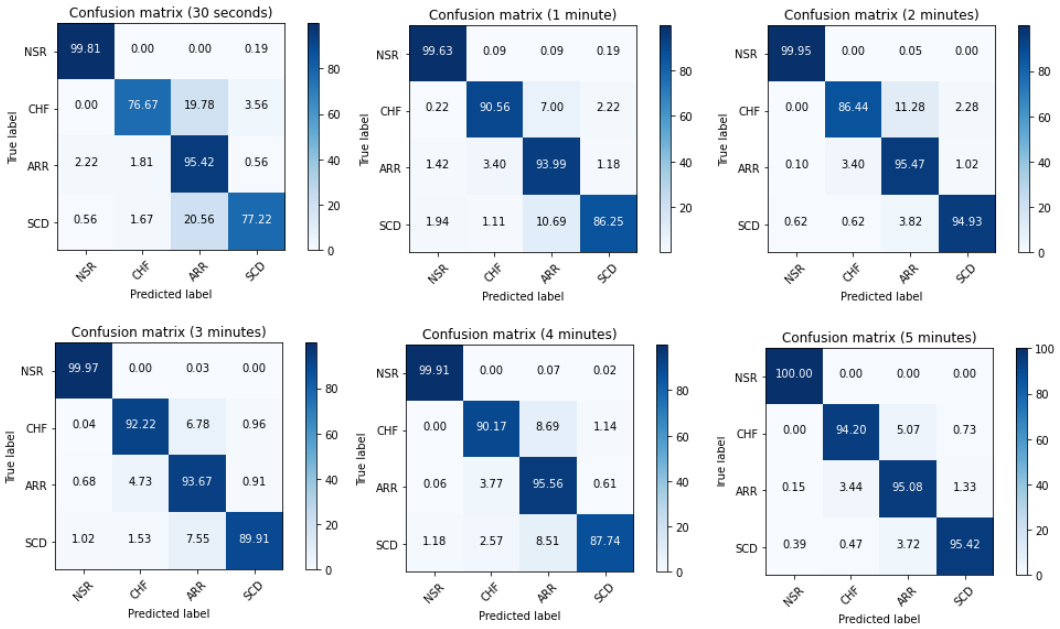


Figure 6



Supplementary Table 1. First Stage: ECG Segmentation Classification using QT database

Subject Wise Cross Validation Accuracy					
Original databases included in the QT Database	**Number of Subjects**	**P**	**QRS**	**T**	**All Segments**
Arrhythmia	11	95.1%	97.4%	93.1%	95.9%
ST_Change	5	97.3%	97.4%	93.7%	96.5%
Supraventricular_Arrhythmia	11	97.0%	97.9%	95.4%	97.1%
Normal_Sinus_Rhythm	10	95.2%	98.1%	94.2%	96.2%
European_ST_T	33	93.7%	96.6%	89.9%	94.4%
Sudden_Death	20	93.3%	96.2%	85.2%	92.8%
Long_Term_ECG	4	92.9%	97.9%	88.3%	93.7%
Total	94	94.5%	97.0%	90.5%	94.8%



Supplementary Figure 1. Confusion Matrix across different time intervals for ECG segmentation classification using Normal Sinus Rhythm (NSR); Congestive Heart Failure (CHF); Arrythmia (ARR); Sudden Cardiac Death (SCD) Databases.

CRediT authorship contribution statement

M.S. Haleem: Data curation, Formal analysis, Investigation, Validation, Writing - original draft, Writing - review & editing. **R. Castaldo:** Data curation, Formal analysis, Investigation, Validation, Supervision, Writing - original draft, Writing - review & editing. **S. M. Pagliara:** Data curation, Investigation, Supervision, Writing - review & editing. **M. Petretta:** Investigation, Writing - review & editing. **M. Salvatore:** Investigation, Validation, Writing - review & editing. **M. Franzese:** Supervision, Writing - review & editing. **L. Pecchia:** Conceptualization, Supervision, Writing - original draft, Writing - review & editing.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:
